A Physics-of-Failure Approach for Common Cause Failures Subject to Age-Related Degradation

Taotao Zhou[a], Enrique López Droguett[a,b], and Mohammad Modarres[a]
[a] Center for Risk and Reliability, University of Maryland, College Park, MD, USA
[b] Department of Mechanical Engineering, University of Chile, Santiago, Chile

Abstract: This paper presents a physics-of-failure approach to model the common cause failures (CCFs) by directly or indirectly measuring and integrating the component degradation evolutions inferred from condition monitoring data. The CCF impacts are characterized based on the conventional parametric model, but unlike the parametric CCF models, the parameters are derived as a function of time based on the estimated degradation states. As such, the proposed parametric CCF estimation is specific to the component being analyzed and is dynamic over lifetime service. The component degradation evolution is characterized by a state-space based degradation model that is built based on the informative features extracted from condition monitoring data. In this study, the β-factor model is adopted without loss of generality, and the component degradation states are estimated using the sensor monitoring data via a recursive Bayesian approach. The validity of the proposed approach is demonstrated by the sensor monitoring data acquired from a special-purpose experiment involving redundant centrifugal pump systems. The results demonstrate the dynamic characteristics of CCF and the significant effects of age-related degradation on the likelihood of CCF. This study introduces physical evidences to the CCF research and provides a component-specific study to validate the significance of CCF. This study also introduces a new way to quantify CCF impacts and would work as a basis for the multi-unit Probabilistic Risk Assessment (PRA).

Keywords: Common Cause Failures, Condition Monitoring, Age, Degradation, Centrifugal Pump.

1. INTRODUCTION

The term common cause failure (CCF) events encompass multiple component failures nearly concurrently due to the possible mechanisms that directly impair the component capacities to perform the design function [1]. The CCF events have been the well-recognized contributor to risks posed to the safe operation of nuclear power plants. Considerable research efforts have been devoted to parametrically model the CCF impacts, referred to as CCF models. In the state-of-the-art parametric CCF models [2] (i.e., β-factor model, the α-factor model and the multiple Greek letter model), the CCF events are characterized by some static CCF parameters that need to be quantified through statistical analysis based on historical observations and engineering judgment [3, 4]. However, these CCF models suffer from several major limitations:

- The models are mainly developed based on generic experience and are usually not specific to the operating components.
- The number of observed failure events in nuclear power plants is limited, especially for the events involving multiple failures.
- There are difficulties to model dependencies in asymmetrical components and to account for the dependencies among the components within multiple common cause component groups.

The implicit assumption of these CCF models is constant failure rate where the failures are treated as fully random without consideration of the degradation effects. The validity of this implicit assumption is debatable, as the nuclear industry is faced with concerns due to plant aging and plant life extension where effects of CCF would be paramount [5, 6]. The importance of aging impacts of CCF on plant risks is also evident from the historical operational experience [7]. However, it is still an open and challenging issue to properly consider the aging impact on the CCF modeling, which constitutes the primary objective of this paper.

This paper develops a physics-of-failure approach to modeling degradation-related CCF events by integrating the component degradation evolution that can be characterized through condition monitoring data. It is first assessed the component degradation by constructing a degradation index based on extracting informative features from the condition monitoring data. Then a state-space based degradation model is built to describe the component degradation evolution considering the variations both within and across components. Thereafter, the CCF impacts are estimated based on the detected degradation evolution and the CCF β-factor model is adopted without loss of generality. At each time step, the β-factor for CCF probability is estimated as the fraction of the degradation states of multiple components that simultaneously exceed each component's endurance to degradation. The estimation of the β-factor for CCF probability, however, follows the conventional parametric CCF model. Accordingly, the scope of the parametric CCF model is dynamic over lifetime service rather than static.

The validity of the proposed approach is demonstrated by the sensor monitoring data acquired from a special-purpose experiment involving redundant centrifugal pump systems at the University of Maryland. The β-factor for this redundant pump systems are estimated by combining the general degradation property with the real-time sensor monitoring data. No maintenance-based rejuvenation is assumed, which follows the state-of-the-art practice of degradation modeling.

The paper is organized as follows. Section 2 briefly discusses the proposed approach to modeling CCF through integrating component degradation evolution. Section 3 presents the experimental study and CCF estimation results. Section 4 presents the conclusions.

2. SUMMARY OF PROPOSED APPROACH

It is proposed to model the CCF for components under age-related degradation by integrating the component degradation evolutions inferred from condition monitoring data. This is a physics-of-failure approach consisting of two parts. The primary objective is to advance the state-of-the-art CCF research by exploiting the recent advances in sensor-based techniques and computational capabilities. Section 2.1 discusses Part 1, the overall degradation assessment. Section 2.2 discusses Part 2, estimation of the β-factor for CCF probability.

2.1. Degradation Assessment

The first part aims to assess component degradation and build a state-space based degradation model based on the sensor monitoring data. In general, the condition monitoring data [8] could be directly or indirectly correlated to the severity of the underlying degradation process. However, it is difficult or even impossible to identify the physical signals that directly characterize the underlying degradation process, as the engineered components become more complex [9]. The signal processing techniques and machine learning techniques [10, 11, 12] are usually needed to extract fault relevant features [10] from the raw signals and ultimately utilized to develop the degradation index [13]. Thereafter, the degradation evolution is usually modeled as a continuous stochastic process according to a physics-based degradation model or some functional form referred to as the empirical degradation model based on the constructed degradation index. In this study, the degradation process is modeled by one of the most common stochastic processes referred to as general path model [14]. The parametric function is assumed to be $Y_k^s = f(k; \boldsymbol{X}_k^s, \varphi)$, where Y_k^s is the degradation state of the s^{th} component at the time step k, $\boldsymbol{X}_k^s$ is a vector of model parameters that is usually treated as a vector of random variables to account for unit-to-unit variability, and φ is an independent and identically distributed (i.i.d.) random error term. Herein, we assume the initial degradation state is zero without loss of generality.

A state-space model is then built to describe the dynamics of the degradation process [15, 16]. The degradation model parameters are assumed to be unobserved states that evolve over time as a random walk process, so as to capture the variation across components. The variability within each component itself is considered by the observation noise. For the s^{th} component involved in the correlated group, the state-space model is applied to track the degradation evolution in terms of the state function and observation function.

State function: $$\boldsymbol{X_k^s} = \boldsymbol{X_{k-1}^s} + \boldsymbol{V} \rightarrow \mathrm{p}(\boldsymbol{X_k^s}|\boldsymbol{X_{k-1}^s}) \tag{1}$$

Observation function: $$Y_k^s = f(k; \boldsymbol{X_k^s}, \varphi) \rightarrow \mathrm{p}(y_k^s|\boldsymbol{X_k^s}) \tag{2}$$

where $f(k; \boldsymbol{X_k^s}, \varphi_k)$ is the degradation model, $\boldsymbol{X_k^s}$ is the state vector of the s^{th} component that is assumed as the hidden Markov process; Y_k^s is the observation (i.e., degradation index) of the s^{th} component that is conditionally independent given the hidden process; $\mathbf{V_s}$ is the i.i.d. process noise vector; φ is the i.i.d. observation noise; k is the time step; $\mathrm{p}(\boldsymbol{X_k^s}|\boldsymbol{X_{k-1}^s})$ is the transition distribution; and $\mathrm{p}(Y_k^s|\boldsymbol{X_k^s})$ is the observation distribution.

2.2. CCF Estimation

The occurrence of CCF would be indicated by the concurrent degradation state exceedance of the endurance to degradation. This is consistent with the state-of-the-art degradation modeling that a component failure is defined as the point at which the degradation state exceeds a predetermined level of endurance to degradation. Therefore, the CCF impacts would be characterized by the fraction of multiple exceedances of the endurance to degradation. This follows the conventional parametric CCF model and further extend the scope of the parametric CCF model to be dynamic over the service lifetime rather than being static.

With the real-time sensor monitoring data of plant-specific components, one could achieve the specific β-factor estimate by combining the general degradation property with the sensor monitoring data. To do this, the state-space model in Section 2.1 is further utilized such that once the sensor monitoring data are collected from an operating component, the hidden states can be inferred to calibrate the estimate of CCF in real time. In this study, the recursive Bayesian updating method is implemented with the particle filtering algorithm [17] to estimate the posterior probability density function (pdf) of the degradation state of the s^{th} component $\mathrm{p}(\mathbf{X_k^s}|\mathbf{Y_{1:k}^s})$ given the observations. At each time step, the samples obtained from the resampling process could be treated as the realizations of the degradation state for each component, and hence can be used to estimate CCF.

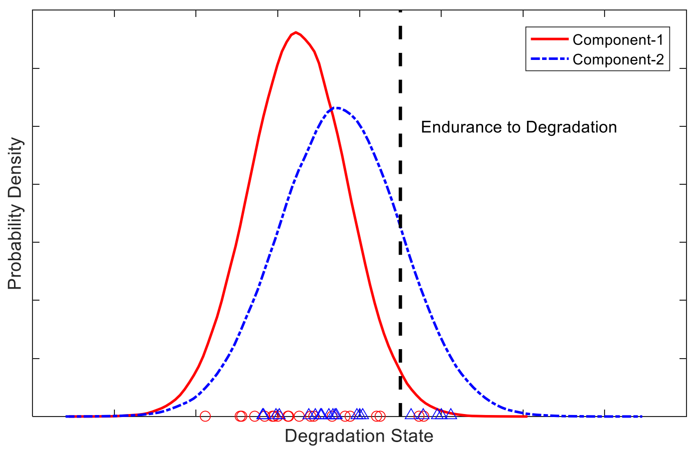

Figure 1: Characterization of CCF with the Components' Degradation States

Consider a two-component system at the time step k as an illustrated in Figure 1. The degradation states for component 1 and component 2 are respectively realized by the N samples $\mathrm{x}_{1:N}^{(1,k)}$ denoted by circles and the N samples $\mathrm{x}_{1:N}^{(2,k)}$ denoted by triangles. The endurance to degradation L_f is treated as the same for both components, as is the convention of CCF. Then the β-factor at each time instant k is estimated as the fraction of dependent failures involving more than a single component as shown in Equation (3), where the denominator denotes the number of all failures and the numerator denotes the number of dependent failures:

$$\beta_k = \frac{\sum_{j=1}^{N}\left\{I\left[2,\ \sum_{s=1}^{2} I\left(x_k^{(s,j)}, L_f\right)\right]\cdot \sum_{s=1}^{2} I\left(x_k^{(s,j)}, L_f\right)\right\}}{\sum_{j=1}^{N}\left\{I\left[1,\ \sum_{s=1}^{2} I\left(x_k^{(s,j)}, L_f\right)\right]\cdot \sum_{s=1}^{2} I\left(x_k^{(s,j)}, L_f\right)\right\}} \quad (3)$$
$$s = 1, 2; j = 1, \dots, N.$$

where β_k is the estimate of β-factor at the time step k, N is the total number of samples, $x_k^{(1,1:N)}$ is the realization of the degradation state of component 1 at the time step k, $x_k^{(2,1:N)}$ is the realization of the degradation state of component 2 at the time step k, L_f denotes the endurance to degradation, $I(\cdot)$ is the state indicator function, which equals 1 for component failure when $x_k^{(s,j)}$ is greater than L_f, and otherwise equals 0, indicating component survival.

3. EXPERIMENTAL DEMONSTRATION

3.1. Experimental Description

To demonstrate the proposed approach, a special-purpose experiment was designed at the University of Maryland. As an active component susceptible to CCF [18], the centrifugal pump was chosen for this case study and three redundant centrifugal pump systems were tested from brand-new condition to full failure inside a temperature chamber as displayed in Figure 2. The pump degradation and failure were exposed to recirculated seawater at elevated temperature. Accordingly, the common-cause dependencies among the pumps were rooted in the same component configuration, the same operating practice, and common intra-environmental conditions (i.e., elevated temperature and corrosive seawater) and inter-environmental conditions (i.e., elevated temperature).

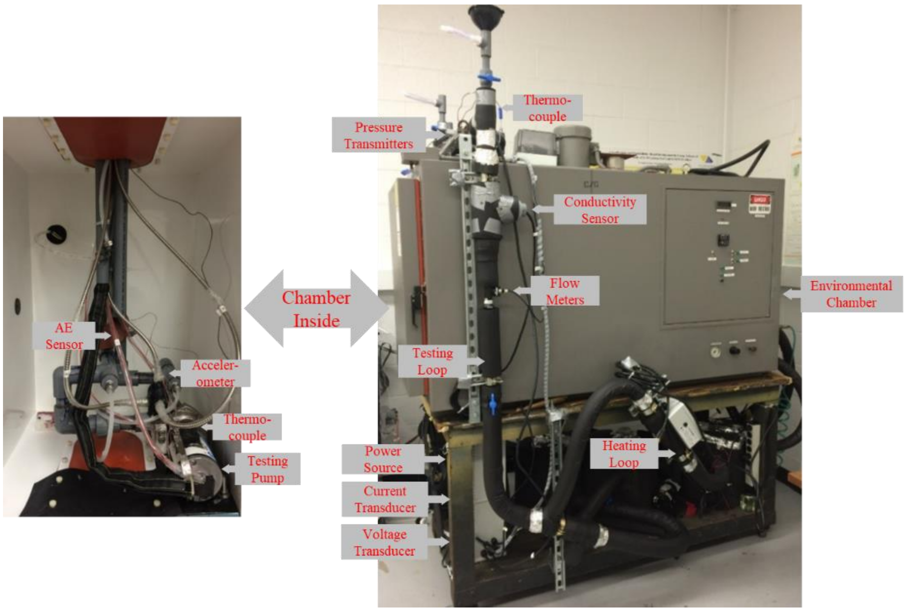

Figure 2: Test Rig and Instrumentation

The entire testing profile is categorized into three phases (i.e., Phase-1, Phase-2 and Phase-3) as shown in Figure 3 given the changes of system configuration. Phase-1 involved a three-pump redundant system from the beginning to 1714 hours of operation. With Pump-1 failed, it then proceeded to Phase-2 involving a two-pump redundant system until 4414 hours of operation. After Pump-3 failed, Phase-3 was with only Pump-2 until 4863 hours of operation. Note that only Phase-1 and Phase-2 are of interest for CCF events.

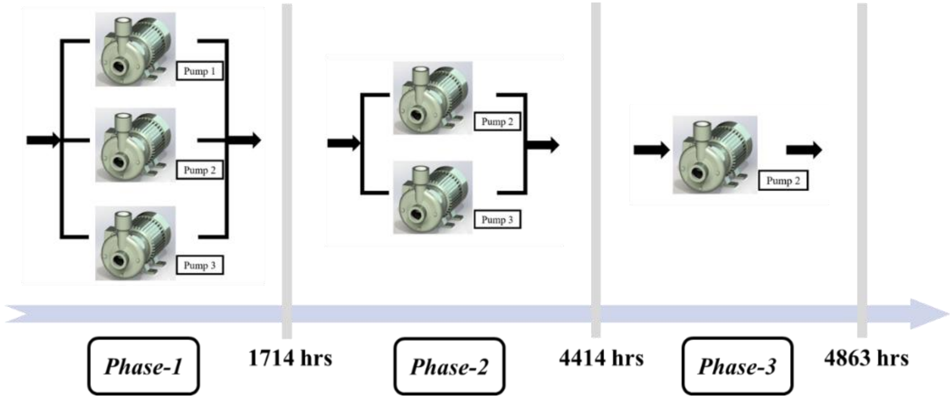

Figure 3: Testing Profile with Three Phases

The pump condition is monitored using the diverse sensors distributed through the test rig as displayed in Figure 2. Failure analysis was conducted after the experiments to identify the root causes: Pump 1 was failed by the fatigue mechanism leading to seal fracture; Pump 2 was failed by the fretting corrosion occurred on the contact surface between the mechanical seal and the rotating shaft; Pump 3 was failed by the pitting corrosion occurred on the contact surface between the mechanical seal and the rotating shaft. The degradation profiles of the three pumps are developed as shown in Figure 4, based on the features contained in the pump efficiency data derived from the four measured operational characteristics: electric current, electric voltage, differential pressure and flow rate. Examination of the degradation profiles indicates that the same functional relationship (i.e., a power function) could be applicable to characterize the pump degradation behaviors associated with any of the three failure mechanisms. Thereafter, a state-space model is built and the sensor monitoring data collected from an operating pump is utilized to infer the hidden states and ultimately to calibrate the estimate of CCF in real time.

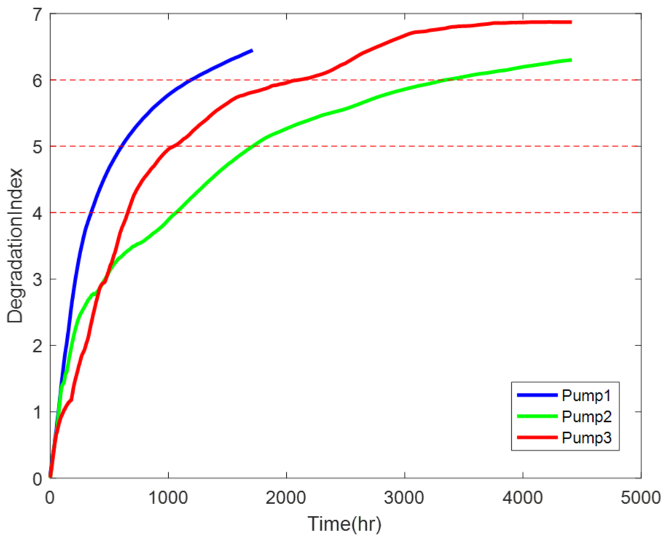

Figure 4: Degradation Profiles of the Three Pumps

3.2. Results and Observations

As an illustrative example in Figure 5, the degradation state of each pump at 1500 hours of operation is estimated and characterized by six thousand samples. This respectively indicates the number of occurrence for the possible degradation states for the three pumps. Then the CCF at 1500 hours of operation would be estimated based on the fractions of concurrent exceedance of failure threshold as discussed in Section 2.

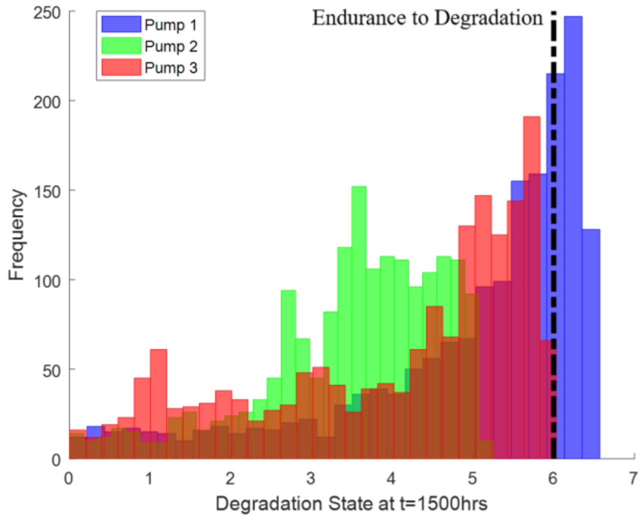

Figure 5: Degradation States of the Three Pumps at 1500 Hours of Operation

With newly acquired sensor monitoring data at each time instant, the degradation state of each pump would be estimated and utilized to update the CCF estimate. As shown in Figure 6, the CCF estimates for Phase 1 and Phase 2 are summarized assuming no maintenance-based rejuvenation. This captures the dynamic features of CCF due to the different failure mechanisms underlying each pump and system configuration changes. Some important observations are discussed as below:

- The β-factor starts from zero and approaches one at the end. It is intuitive to note that the redundant pump system would fail eventually without any mitigating actions.
- It appears independent failure is dominant in Phase-1, indicating by the low β-factor, because Pump 1 is subject to more likely failure than the other two pumps. This is evident from its shortest experiment duration in Section 3.1.
- The β-factor approaches one in Phase-2, because the pumps degrade without mitigating actions.
- The knowledge of the pump degradation state allows one to determine the time that is required to implement mitigating actions given some critical level of CCF [19]. Suppose the β-factor should be less than 0.05, so that mitigating actions should be taken before 2870 hours of operation.

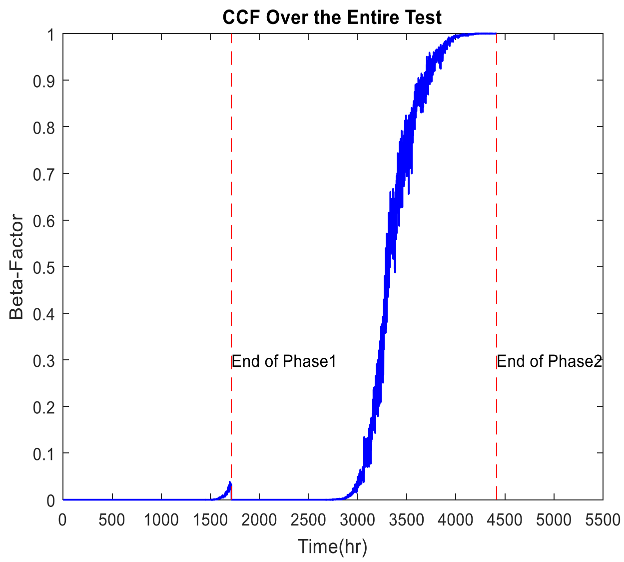

Figure 6: Estimate of β-Factor for Phase-1 and Phase-2

4. CONCLUSION

The paper advances the state-of-the-art CCF research by exploiting the recent advances in sensing techniques and computational capabilities. It was developed a physics-of-failure approach to model the CCF for components under age-related degradation by integrating the component degradation evolutions inferred from condition monitoring data. An experimental case study involving three redundant centrifugal pump systems was presented to demonstrate the approach. The significance of CCF events using a component-specific study was discussed, along with the dynamic characteristics of CCF. The results concluded that the age-related degradation has significant effects on CCF probability. This study introduces physical evidences to the CCF research of nuclear power plant and would work as a basis for the multi-unit Probabilistic Risk Assessment (PRA). Moreover, this study presents a new way to quantify the common cause influences. Integrating the maintenance impacts on the component degradation evolutions is part of our current research to obtain more realistic estimates of CCF probability as components degrade, which allows one to examine the validity of the generally estimated CCF parameters used in the current practice.

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